Journal of Economic Behavior and Organization 172 (2020) 33–56

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Field comparisons of incentive-compatible preference elicitation techniques[☆]

Shawn Cole[a], A. Nilesh Fernando[b,*], Daniel Stein[c], Jeremy Tobacman[d]

[a] Harvard Business School, United States
[b] University of Notre Dame Indiana 45665 United States
[c] IDinsight, United States
[d] University of Delaware, United States

ARTICLE INFO

Article history:
Received 7 May 2018
Revised 4 January 2020
Accepted 20 January 2020
Available online 25 February 2020

JEL classification:
C81
C93
D12
D14

Keywords:
Incentive-compatible elicitation
Experimental methods
Weather insurance
Rainfall insurance
Agricultural extension

ABSTRACT

Knowledge of consumer demand is important for firms, policy-makers, and economists. One common tool for incentive-compatible demand elicitation, the Becker-DeGroot-Marschak (BDM) mechanism, has been widely used in laboratory settings but rarely evaluated for reliability at large scale in the field. In two field experiments (for a new agricultural information service and rainfall index insurance) we compare demand curves estimated from BDM implementations with demand curves estimated from choices at individually randomized fixed prices. In the test (for an agricultural information service) we obtain demand curves from BDM and fixed prices that align closely and are unable to reject equivalence of the demand curves. For the second test (of rainfall index insurance) the results are mixed, with the distributions lining up well at certain points of the demand curve and deviating at others. Overall, we find no evidence for systematic bias. Our evidence suggests that a 'reframed' version of BDM that uses discrete prices may minimize non-standard bidding behavior and is well suited to future experimental work in low-literacy environments.

1. Introduction

Reliable estimates of demand curves matter for private actors and policymakers. Profit-maximizing firms rely on this information to set optimal markups. Charities can use demand curves to optimize their investments. Policymakers seeking to redress externalities require demand estimates to set optimal Pigouvian taxes and subsidies.

However, demand curve estimation using observational data from market settings can be problematic, both because the supply curve is unknown and because the competitive market price may only reveal the willingness to pay (WTP) of the marginal consumer. Becker et al. (1964) introduced a mechanism (henceforth, BDM) that has been used frequently in laboratory experiments to measure participants' valuations of products. This mechanism is attractive because truthful revelation of

☆ We are very grateful to Chhaya Bhavsar, Nisha Shah, Reema Nanavaty, and their colleagues at SEWA, and Paresh Dave, Natu Makwana, and Sachin Oza at the Development Support Center, whose extraordinary efforts made this research possible. Maulik Jagnani, Laura Litvine, Dhruv Sood, Sangita Vyas, Will Talbott, Tarun Pokiya, HK Seo, Niriksha Shetty,Chungeun Yoon, and Alison Lodermeier provided excellent research assistance. We would also like to thank USAID's BASIS program, USAID-DIV, ATAI, 3ie, IGC, Wharton's Dean's Research Fund, and the Division for Faculty Research and Development at Harvard Business School for financial support. All errors are our own.

* Corresponding author.
E-mail address: nilesh.fernando@nd.edu (A.N. Fernando).

https://doi.org/10.1016/j.jebo.2020.01.021
0167-2681/

willingness to pay is the dominant strategy, allowing the construction of the demand curve and even identifying individual valuations. A typical BDM implementation, like the ones used in our work and described below, has four steps. Respondents are informed of the sequence of steps, they report WTP, an offer price is randomly drawn from a distribution, and respondents purchase the good at the offer price if it is less than their stated WTP.

This procedure and equivalent analogues have been used extensively in laboratory and field experiments in economics and marketing.[1] However, demand curves estimated using BDM have rarely been compared to demand curves estimated using a more natural kind of variation: randomly assigned prices. Along other important dimensions, BDM has been subjected to careful methodological scrutiny. First, differences may arise between hypothetical and real-money choices (Camerer and Hogarth, 1999; List and Gallet, 2001). Next, knowledge about the price distribution appears to affect stated valuations (Bohm et al., 1997; Mazar et al., 2014). Finally, there are typically large willingness-to-accept vs willingness-to-pay asymmetries. BDM has the important advantage that, if working as advertised, it detects the price at which each respondent is indifferent between purchase and non-purchase, providing much more information per subject than a fixed-price sale offer. As a consequence, randomizing prices instead of using BDM will almost certainly require many more subjects in order to obtain comparable precision of demand curve estimates.

In practice, the research advantages of BDM might be outweighed by several limitations relative to experiments with randomly assigned fixed-price offers. First, BDM is more complicated. This could lead to more noise in responses and more non-response. Second, BDM respondents might misunderstand the steps described above and erroneously believe BDM involves a negotiation, which could bias BDM WTP estimates down. Third, truthful revelation is only a dominant strategy when agents maximize expected utility (Horowitz, 2006; Karni and Safra, 1987). Finally, BDM respondents must pre-commit to purchase at a certain price, but may not end up following through, invalidating some bids by revealed preference. In light of these considerations, whether BDM performs well in practice is an empirical question.

This paper's main objective is to resolve that empirical question. Although this question has been explored before, previous papers generally test BDM in a closed lab setting with a small sample size, with the notable exception of Berry et al. (2019), which will be discussed below. We believe our paper provides the most comprehensive test yet of BDM against fixed prices, as it conducts the test using data from two field experiments, for three products, and using two different forms of the BDM method, with all tests conducted with a large sample size.

We use BDM to measure demand for a rainfall-indexed insurance product (hereafter, 'WI') and an innovative agricultural information service called Avaaj Otalo (hereafter, 'AO') in two separate field sites in India. Both trials were conducted among farmers at the typical point of sale (usually, their home). For rainfall insurance, BDM was implemented during marketing visits as part of a randomized impact evaluation (Tobacman et al., 2016). For the AO agricultural information service, BDM was implemented during the end-line survey of a different randomized impact evaluation (Cole and Fernando, 2019). Across experiments, we find that a modest 8.1% of BDM respondents provide bids that are later invalidated.

We find that the demand curves implied by BDM and TIOLI frequently align, though there are significant deviations. For AO, we are unable to reject that demand is the same at any point along the distributions estimated using BDM or TIOLI. For rainfall insurance, the story is mixed. For one weather insurance product (a single unit of coverage), BDM elicits a WTP that is on average below that predicted by TIOLI. For a more comprehensive product (four units of coverage), BDM elicits a WTP that is on average higher than that predicted by TIOLI, though equivalence of the distributions cannot be rejected. Moreover, estimated arc price elasticities of demand are similar for both products across methods, with minimal deviations. Moreover, similar to previous studies (Berry et al., 2019; de Meza and Reyniers, 2013) we find that the gap between BDM and TIOLI is reducing in a proxy for risk aversion of the respondent.

Demand elicitation in the AO experiment focused on a discrete set of prices rather than the real line, reducing the possibility of round-number 'effects', de-emphasizing the 'lottery aspect' of BDM and asking the respondents to make choices similar to those in a market setting. Given that this method produced demand that mostly aligned with TIOLI, our results suggest that practitioners should consider the use of this type of 'reframed' BDM mechanism for future field work, particularly in low-literacy environments (de Meza and Reyniers, 2013; Loewenstein and Adler, 1995).

A handful of previous papers have undertaken comparisons between BDM and other demand elicitation techniques in the lab, with mixed results. Bohm et al. (1997) test BDM among university students for a petrol card, using BDM and a market setting. They find that the WTP as measured by BDM is sensitive to the upper bound of the offer price distribution but performs well as long as the upper bound of that distribution corresponds to market prices. Noussair et al. (2004) compare BDM to a Vickrey auction and find that it takes longer under BDM for subjects to learn to make optimal bids. Miller et al. (2011) compare BDM to TIOLI for a cleaning product among Swiss students and consumers. They find that demand measured by BDM is not statistically different from that of TIOLI. de Meza and Reyniers (2013) test BDM versus TIOLI for a candle among London students and find that demand expressed through BDM is higher than via fixed-price offers.[2]

Our experiments are conducted in natural settings for relatively high-stakes purchase decisions. The premium of products we offer ranges from Rs. 99 ($2) to Rs. 699 ($14) for households whose monthly expenditure is, on average, roughly $75.

[1] The original Becker et al. (1964) paper has over 1500 Google Scholar citations, while the phrase "incentive-compatible elicitation" without quotes yields 3800 results. A few recent implementations include Guiteras and Jack (2014), Hoffmann (2009), Yishay et al. (2017), Channa et al. (2019).

[2] See also recent work that uses BDM to study the form of reference dependent preferences (Marzilli Ericson and Fuster, 2011; Heffetz and List, 2014). Expectations as reference points (Kőszegi and Rabin, 2006) implies that the probability distribution over the offer prices in the strategy elicitation should matter for reported WTP.

We only know of two previous efforts to evaluate BDM in the field in a developing country. Banerji et al. (2013) compare both BDM and a k-th price auction to a choice experiment, though they do not evaluate simple TIOLI offers. They find that all three mechanisms result in similar distributions of WTP.

The paper closest to ours, Berry et al. (2019), hereafter, BFG, compares WTP from BDM to demand measured by fixed-price offers for a water filter in Ghana. They find that BDM modestly underestimates WTP when compared to TIOLI. While our strategy is similar to theirs, our results differ: despite comparable or greater power, we do not find that BDM systematically underestimates TIOLI, and instead find mixed results. On the surface, there do not appear to be major differences between the field elicitation procedure used in BFG and ours, though we can highlight a few differences. First, the experiments took place in different countries for very different products. Perhaps the fact that their product was a physical, visible product affected elicitation choices. A second difference is that at village meetings, BFG demonstrated both BDM and TIOLI to all potential purchasers. By contrast, our implementations presented respondents with one choice procedure or the other. Finally, for AO we use a modified version of the BDM mechanism in which participants could only give discrete WTP choices, and this may have contributed to better performance of BDM.

Our experiments take place for multiple products over multiple time periods, while BFG conduct the experiment for one product at one time. Some of our comparisons show BDM underestimating demand compared to TIOLI, others show overestimation, and some agree more closely. We therefore view our experiments as providing a more comprehensive view of the performance of BDM in the field, suggesting that BDM need not underestimate demand in general.

Overall, we conclude that due to (a) the lack of systematic bias, (b) low rates of non-compliance, and (c) the strong alignment of BDM compared to TIOLI in the reframed elicitation method used for AO, BDM is a viable and valuable choice for experimentalists looking to elicit complete demand curves for low cost.

The paper proceeds as follows. Section 2 presents a simple simulation framework that illustrates the trade-offs between BDM and TIOLI demand measurement approaches. Section 3 details our field procedures used to implement BDM. Section 4, the centerpiece of the paper's empirics, compares demand curve estimates from BDM and TIOLI elicitations. Section 5 investigates effect heterogeneity, while Section 6 offers practical guidance from our findings for future work. Section 7 concludes.

2. Simulation framework

Experimentation using BDM and TIOLI methods is useful for learning about consumer valuations of products. Both approaches are incentive-compatible, but BDM may be more efficient than TIOLI because for each respondent BDM provides continuous information – or, in the case of reframed BDM, more discrete information – and TIOLI provides binary information. This section provides illustrative elaboration.

Suppose a firm wants to set a price, p, for a given good so as to maximize profits.[3] Assume further that the true demand function of the firm's potential customers is $D(p)$. A firm might then conduct an experiment to estimate $D(p)$, either nonparametrically or by estimating the free parameters after assuming a functional form. The firm could then use those estimates to calculate an optimal price.

To calibrate the potential benefits of BDM, we simulate this scenario. Suppose that the demand function is in the constant elasticity class, i.e., $D(p) = Ap^{-\epsilon}$, where A is a scale parameter and ϵ is the price elasticity. We fix A and ϵ, and we draw a population of reservation values that gives rise to this demand curve. Then, as if conducting field experiments to estimate demand, we can repeatedly sample from the population and study the properties of estimates of A, ϵ, and profits based on these samples.[4]

For BDM, the estimates of A, ϵ, and profits are straightforward to compute for each sample, as BDM elicits the reservation values themselves: we can regress log demand at each reservation value on the log reservation value. For TIOLI, we assume that k price offers are randomly assigned so as to be evenly spaced across the percentiles of the reservation value distribution (e.g., with $k = 3$, the TIOLI prices are taken to be at the 25th, 50th, and 75th percentiles).[5] Then demand is measured at each of these TIOLI prices, and log demand is regressed on the log of the TIOLI price.

We repeat these calculations for M samples of size N. Denote the estimated elasticities from sample m of size N under the two procedures by $\hat{\epsilon}_m^{BDM}(N)$ and $\hat{\epsilon}_m^{TIOLI}(N)$. For a risk-neutral firm with a constant marginal cost c, profits are $\pi = (p - c)D(p)$, implying the familiar inverse-elasticity optimal markup, $\frac{p-c}{p} = 1/\epsilon$. If an elasticity $\hat{\epsilon}$ is estimated as above and used by some market participant to adopt a price, then that market participant can earn maximal profits of

$$\hat{\pi} = \frac{Ac\left(\frac{\hat{\epsilon}c}{\hat{\epsilon}-1}\right)^{-\hat{\epsilon}}}{\hat{\epsilon} - 1}$$

To illustrate, we assume the underlying true demand function has $A = 100$ and $\epsilon = 2$; we create a population of 10000 people with reservation values giving rise to the corresponding demand curve; and we let $c = 1$ and $k = 5$. Then for each

[3] Nonprofits, governments, and social entrepreneurs might want to maximize different objectives, and the framework here could be adapted accordingly.

[4] This paper's experimental work should be viewed as analogous to a single sample.

[5] This choice may differ from the optimally informative set of TIOLI prices, but it advantages TIOLI relative to most field contexts where little is known ex ante about the distribution of reservation values. In principle it would be possible to optimize the number k of TIOLI price points. Given a fixed sample size N, this trades off precision across the distribution with precision at each price. Berry et al. (2019) randomized TIOLI prices among rounded values near the 25th, 50th, and 75th percentiles of the distribution of BDM bids in pilot villages.

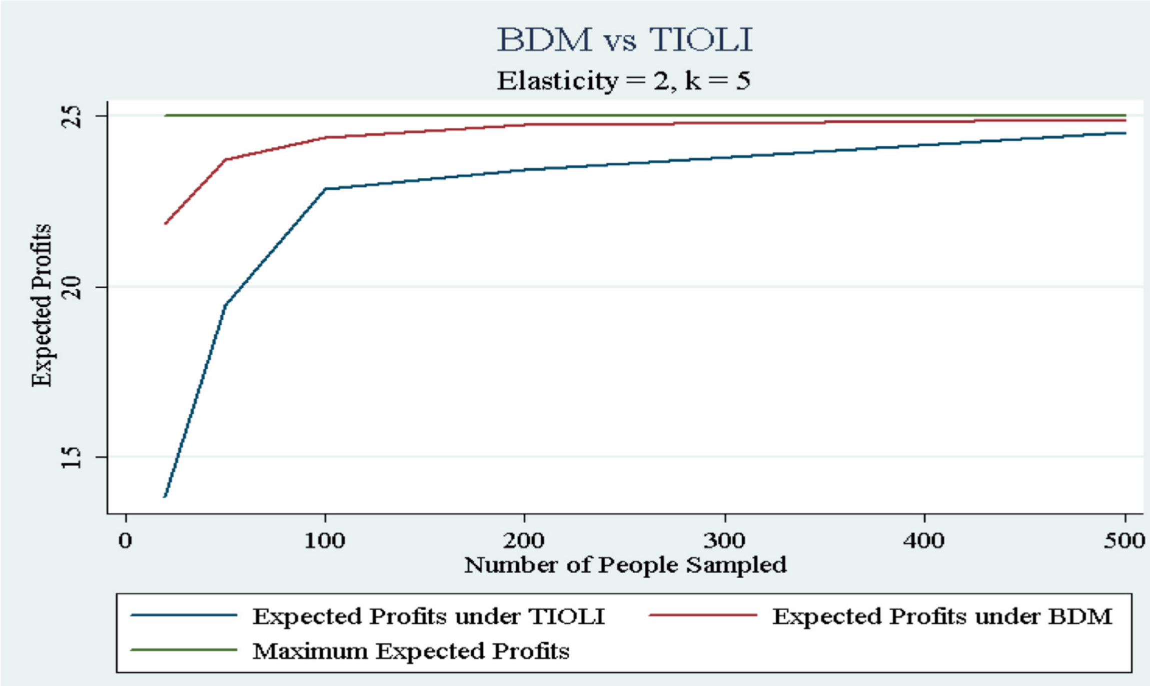

Fig. 1. Simulated expected profits under BDM and TIOLI. *Notes:* This figure reports the results of simulated experiments using BDM and TIOLI methods. The horizontal axis is the sample size, while the vertical axis reports the implied expected profits. As the experimental sample grows, both methods approach profit maximization in expectation, but BDM performs better than TIOLI, especially for small experimental samples. The variable k is the number of fixed prices, at equally-spaced percentiles of the reservation value distribution, used to implement TIOLI.

of several values of N, we draw $M = 100$ samples. Fig. 1 reports the expectation of $\hat{\pi}$ across these simulated samples. For this parameterization, maximal expected profits equal 25. As the simulated samples grow in size, Fig. 1 reports that $\hat{\pi}$ from both BDM and TIOLI converges to this theoretical maximum.

Fig. 1 also shows that a profit-maximizing firm using experimental data from small samples to set prices could reliably achieve higher expected profits using BDM relative to TIOLI. BDM expected profits converge very rapidly to the theoretical optimum as sample size grows, a consequence of the additional information revealed via BDM elicitation. The standard deviation across samples of expected profits is lower for BDM than for TIOLI, as well.

This framework could be extended in a number of ways, and we view the following three as especially natural. First, Bayesian inference could be undertaken based on information from the BDM and TIOLI procedures.[6] Second, the assumption of log-linear demand could be relaxed.[7] Third, the simulation framework could incorporate potential disadvantages of BDM like confusion, non-response, or systematic bias and explicitly compare them with the potential advantages of BDM calibrated above.

The practical importance of these potential extensions can be informed by real-world evidence that compares demand curves estimated using BDM and TIOLI elicitations. In the next sections, we report such evidence, from field experiments which turn out to imply that the qualitative results from the simple simulation framework may suffice to recommend BDM in many areas of application. In Section 6, we take stock of both the theoretical advantages of BDM and our empirical findings to provide guidance for future work.

3. BDM in the field

This section outlines the field procedures used for the two experiments. We describe the rainfall insurance experiment first and the agricultural information service experiment second. Further details can be found in Appendix B.

[6] More statistical efficiency is likely to be available with Bayesian methods, but some practitioners may begin trying to learn about their markets with simple frequentist demand estimation methods like those studied here.

[7] Our view is that the log-linearity assumption makes the performance of TIOLI relatively insensitive to the choice of its k price points. With log-linear demand, TIOLI data reliably allow inference about the elasticity that's relevant for optimal pricing: In general, the elasticity that's relevant is the one local to the optimal price that is chosen. With log-linearity, the elasticity is constant, so estimating it anywhere along the demand curve will work. BDM will be likely to have observations near the critical location on the demand curve, even if the demand curve is not isoelastic.

3.1. Rainfall insurance

Elicitation of WTP for rainfall insurance was undertaken in the context of a multi-year randomized controlled trial of rainfall insurance in Gujarat, India (Tobacman et al., 2016; Cole et al., 2014; 2013), conducted in conjunction with the Center for Microfinance (CMF) and the Self-Employed Women's Association (SEWA). The rainfall insurance policies studied in this paper were offered by the Agricultural Insurance Company (AIC) of India. The precise terms varied by year and location, but policies always offered payouts for deficit or excess rainfall in different parts of the growing season. SEWA members in the study area tend to be poor, relying primarily on agriculture for their livelihoods.

BDM and TIOLI discounts were undertaken by SEWA staff as part of their door-to-door rainfall insurance marketing efforts. During rainfall insurance marketing in 2010 and 2011, a total of 4129 of these door-to-door visits were randomly assigned to conduct either BDM or TIOLI.[8]

During the visits, the SEWA marketers explained the concept of rainfall insurance and the purpose of the visit, and they answered questions from the potential respondents. Once participants expressed comfort with the information, they received scratch cards with their names pre-printed (see Figure A.1). Participants first scratched off the top panel of the card, which indicated a (randomized) assignment to a take-it-or-leave-it offer or participation in BDM. The BDM assignment was (randomly) for either a single unit of insurance or a bundle of four insurance policies.[9] The four policy bundle can simply be thought of as a policy with more coverage: it had a list price of four times the single policy premium and provided four times the payout of the single policy for all realizations of the rainfall index.

If the fixed-price discount was offered, this was also randomly-assigned to be valid for either one unit of insurance or a bundle of four policies.[10] We offered only two fixed prices per product, with the intention of maximizing power for comparison with BDM at each fixed point. If the participant expressed interest but didn't have the money on hand, a SEWA representative would return in around two weeks to complete the sale.

If the participant received the chance to participate in the BDM exercise, the SEWA team then explained the BDM procedure. The BDM elicitation was practiced for a SEWA napkin, which had a market value of Rs 10.[11] The napkin BDM was concluded on the spot (with cash and item changing hands, if the bid exceeded the offer price), to show exactly how the game worked. The sales team then repeated the procedure for insurance. The steps for the BDM method were as follows:

1. Participant states the maximum amount they are willing to pay for the insurance policy. This "bid" is recorded by the facilitator.
2. Participant scratches off the random "offer" price from the scratch card.
3. If the offer is less than the bid, then the participant purchases the insurance at the offer price. If the offer is greater than the bid, the participant cannot purchase policies during that marketing visit, though she or he could purchase the insurance at full price through an agent or SEWA sales team member at another time.

After stating their insurance bids, participants were reminded that a bid above the offer price was an agreement to purchase insurance and that if the bid was below the offer price there would be no sale. In order to make sure that the BDM bid did not reflect short-term liquidity fluctuations, participants were told that if they didn't have the money to purchase insurance on the same day, a SEWA representative would return in two weeks to complete the sale if their bid exceeded the offer price. Before scratching off the offer, participants had a chance to adjust their bid, but once the offer was scratched off they could no longer change their bids.

The distribution of offered prices had support ranging from zero to the market price.[12] Respondents were told the market price as well as this range. The distribution of offer prices was skewed downward, with more lower-priced offers than higher-priced offers.[13] All participants, after making choices in the experimental TIOLI and BDM tasks and realizing BDM offer prices, could later purchase additional insurance policies for full price. Few participants had additional demand.

3.2. Agricultural information service

The Avaaj Otalo (AO) platform is a mobile phone-based service that provides on-demand information on agricultural best practices to farmers. Information can be requested and shared by farmers who have access to this toll-free service. The service also includes weekly push-content, which includes detailed agricultural information on weather and crop conditions that are delivered through an automated voice message. A randomized controlled trial was carried out between 2010 and 2013 across 40 villages in Surendranagar district, Gujarat to understand demand for this service and its impact on a variety of agricultural outcomes (Cole and Fernando, 2019). The study was conducted in partnership with the Development Support Center (DSC), an NGO with decades of experience in providing agricultural extension throughout Gujarat.

---

[8] Rainfall insurance had been sold by SEWA in the study area since 2006, so the participants may have had some previous awareness of rainfall insurance.

[9] Randomization was done independently each year. If participants declined to scratch off the cards, we have the data on whether they would have been allocated to BDM or TIOLI, and what their BDM offer price would have been if applicable. Those assigned to TIOLI are coded as not purchasing, and those assigned to BDM are coded as a bid of 0. We also provide alternative specifications in the appendix in which we drop people who refused to participate.

[10] TIOLI for four policies was only offered in 2011.

[11] The napkin exercise was conducted only in 2010.

[12] As the insurance products changed slightly from year to year, the market price (and therefore the support) is different in 2010 vs. 2011.

[13] This was to increase power for a parallel trial of the effectiveness of insurance, described in Tobacman et al. (2016).

In the context of this experiment, the WTP exercises were carried out at the same time of the final round of surveying, in June, 2013. The overall Avaaj Otalo sample includes 1200 study respondents who were chosen at random from a list of over 1700 DSC clients who cultivated cotton, owned a mobile phone, and were the chief agricultural decision-makers in their households. The BDM versus TIOLI experiment was performed at endline, when 1099 households were located and surveyed. This sample of 1099 includes households that received AO for free as part of the RCT as well as those in the control group.

Respondents were randomly assigned envelopes that determined whether they would receive BDM or TIOLI.[14] All farmers were read a marketing script explaining the features of AO before they made any choices. In the AO case, BDM took the form of a modified procedure in which only a handful of discrete bid prices were allowed (as opposed to the open question in the rainfall insurance example.) This particular formulation of BDM is sometimes termed 'reframed' BDM or 'rBDM' and has been implemented in lab settings with successful results (Loewenstein and Adler, 1995; de Meza and Reyniers, 2013).

In the event that the envelope stated that the respondent was assigned TIOLI, their envelope contained their fixed-price offer. The respondent then had the opportunity to either purchase the service or decline the offer.

If the envelope chosen indicated that the respondent was assigned to the BDM elicitation, the surveyor first gave a brief explanation of how the procedure would work. Following this, the surveyor offered AO to the respondent at decreasing price points, ranging from Rs. 490 to 0. If the respondent agreed to buy AO at a certain price *(bid price)*, the surveyor would then call the field office and inform the phone operator of the respondent's bid price and the unique envelope ID that was used. In the AO case (in contrast to weather insurance) the respondent was not told the market price, which did not exist for this service newly introduced by the authors (Cole and Fernando, 2019).

Having recorded the envelope ID and the respondent's bid price, the phone operator would then tell the surveyor which scratch card had been pre-assigned to that respondent. The surveyor would then provide the appropriate scratch card to the respondent, who would scratch it to reveal the offer price. Respondents were told that offers were drawn randomly; in practice, they were drawn uniformly from Rs. 40, 90, 140, 190, and 240. If the offer price was lower than the bid price quoted by the respondent, the participant would purchase the service at this discounted offer price. If the offer price were higher than the bid price, the exercise ended, and the respondent could not purchase the AO service.

If the respondent purchased the service, the surveyor collected payment and the details required to activate the service on the farmers' phone.

Details on the sample and elicitations conducted can be found in Table 1.

As it is well-known that anchoring can affect willingness-to-pay (Simonson and Drolet, 2004; Ariely et al., 2003), it is important to note that all choices in this experiment had explicit anchors. Since most real-world purchasing choices (such as fixed prices in a shop) do have natural price anchors, demand decisions in this context seem most relevant. For weather insurance, participants in both the BDM and TIOLI arms were told the market price of the product (as set by the insurance company). Since AO was a new product, there was no established market price. However, the step-wise elicitation of BDM conducted for AO provides natural anchors, while the TIOLI price is itself an anchor. We believe that the existence of anchors across all mechanisms makes the results comparable.

3.3. Compliance

Participation in all exercises was completely voluntary and the respondent was informed of the possibility to opt out at any point. The BDM exercise has a number of steps that must be followed in order to elicit a plausibly accurate WTP. When undertaking a large implementation of BDM in the field as opposed to a laboratory, there are likely to be deviations from the ideal execution of the exercise.

When the BDM offer price is revealed, this is supposed to determine the purchase decision of the participant. If the offer price is lower than the stated WTP, they should purchase (and should want to purchase) the product at the offer price. If the offer price is higher than the stated WTP, then no sale occurs. However, slippage is possible: in some cases, participants may fail to purchase the product despite having $bid \geq offer$, and in other cases, participants may purchase the product even though the offer price was higher than their stated WTP.

Table 2 reports compliance rates in the implementations we study. When completing the BDM exercise for one insurance policy, the participants did not purchase despite a stated WTP above the offer price 5.0% of the time, and purchased even though the offer price was higher than their expressed WTP 1.5% of the time. For the four policy sale, the non-compliance rate was higher: 8.2% did not purchase when the offer price was below their WTP, while 0.5% purchased even though the offer price was higher than WTP.[15] For AO, 6.5% did not purchase when their bids exceeded their offer prices, and no one ended up purchasing if the offer price was above their WTP.

What explains non-compliance? Anecdotally, participants stated that their non-compliance was due to liquidity constraints, as they were unexpectedly unable to gather the money to purchase the product. Indeed this is supported in the

[14] If farmers refused to participate before the drawing of envelopes, they never received assignment to BDM or TIOLI. For the purposes of analysis, they were randomly allocated to BDM or TIOLI based on the proportion of envelopes. Those assigned to TIOLI are coded as not purchasing, and those assigned to BDM are coded as a bid of 0. Results are unchanged if we instead drop them from the analysis.

[15] In the insurance context, when participants purchased despite reporting WTP that was less than the offer price, they sometimes ended up paying the offer price (due to errors in executing the BDM protocol), and other times they paid the list premium (which was allowed).

Table 1
Summary statistics.

Panel A: Sample for BDM vs TIOLI Comparison				
	Rainfall Insurance			Agricultural Information (AO)
Year	2010	2011	Total	2013
Assigned to a Fixed Price Offer	1083	1380	2463	294
Assigned to BDM Procedure	1050	682	1732	805
Provided Valid BDM Bid	611	274	885	533
Provided Invalid BDM Bid	46	20	66	52
Declined to Participate	440	408	848	220
Assigned BDM for 1 Policy	556	346	902	-
Assigned BDM for 4 Policies	494	336	830	-
Market Price	150	195	345	230
Average WTP for 1 Unit (as % of market price)	40%	26%	35%	46%
Average WTP for 4 Units (as % of market price)	26%	16%	22%	-
TIOLI Fixed Price (Rs)	1 Policy 2010	1 Policy 2011	4 Policy 2011	AO
40	0	0	0	58
90	0	0	0	62
99	0	270	0	0
100	532	0	0	0
130	551	0	0	0
140	0	0	0	61
149	0	278	0	0
150	0	280	0	0
190	0	0	0	57
240	0	0	0	56
499	0	0	274	0
599	0	0	278	0

Notes: This table gives summary statistics for sample population. “BDM Offered” means a household was visited and offered the chance to participate in BDM. This means BDM was conducted for one policy or a bundle of four policies. “Provided Invalid Bid” means the participant did not actually pay the rupee amount for their quoted bid price even though they were obliged to. These respondents are removed from the regressions. For AO, assignment of BDM or TIOLI was done in the field, so people who refused to participate were randomly allocated to BDM vs TIOLI based on the ex-ante probability. The refusals category also includes some people who selected BDM but then refused to provide a bid. Bids of zero were assigned when a household was offered the chance to participate in BDM but declined. In the case of AO, the market price is the break-even cost computed by the field team and does not include any mark-up. The product was not offered commercially except in limited pilots by an NGO. In the insurance case, the market price is the premium determined by the insurer. For rainfall insurance, the premium per policy was constant across locations in all years except for 2009, where it varied by location. The premium listed for 2009 is the average premium among the sample. The average WTP for 1/4 policies is the WTP divided by the total premium.

Table 2
BDM elicitation non-compliance rates.

Year	Weather Insurance						Agricultural Information Service		
	One Policy			Four Policies			One Subscription		
	Supposed to Purchase, But Did Not	Not Supposed to Purchase, But Did	Number of People Providing Bids	Supposed to Purchase, But Did Not	Not Supposed to Purchase, But Did	Number of People Providing Bids	Supposed to Purchase, But Did Not	Not Supposed to Purchase, But Did	Number of People Providing Bids
2010	5.5%	1.2%	330	7.8%	0.7%	281	-	-	-
2011	4.0%	2.0%	151	8.9%	0.0%	123	-	-	-
2013	-	-	-	-	-	-	6.5%	0.0%	805
Total	5.0%	1.5%	481	8.2%	0.5%	404	6.5%	0.0%	805

Notes: The “Supposed to Purchase” column lists the percentage of BDM participants who expressed a WTP greater than the offer price but did not purchase. The “Not Supposed to Purchase” column lists the percentage of BDM participants who expressed a WTP less than the offer price but purchased anyway.

data, as noncompliance is positively correlated with the offer price. For AO, we have additional data on household characteristics of participants, and explore whether these characteristics are associated with non-compliance. We do not find significant relationships with hypothesized correlates such as literacy, education, and age.[16]

There is some question about how to treat BDM bids that are subsequently invalidated by revealed preference. Given that these bids clearly do not represent underlying ‘true’ preferences, it seems unlikely that a practitioner would include them when constructing a demand curve. Therefore, we do not include these non-compliant bids when comparing BDM to TIOLI.[17] However, the problem remains that there are likely other bids that would have been invalidated had a different

[16] These results are detailed in Appendix Table A.3.

[17] In Appendix Tables A.4–A.6 we provide robustness checks in which these bids are included using varying assumptions on what they represent.

offer price be drawn. Overall, the existence of non-compliant BDM participants undermines the credibility of the approach, and, therefore, in practice the elicitation procedure must be implemented carefully to ensure that participants make credible bids.

4. Main results: comparison of BDM to TIOLI

In this section we assess the comparability of BDM with fixed-price TIOLI offers. Conceptually, BDM and TIOLI both have advantages and limitations for practitioners' efforts to learn about demand. BDM is somewhat difficult to explain and may result in slippage but can provide an exact value for each respondent's WTP. By contrast, TIOLI more closely resembles many real-world purchase decisions, but each TIOLI offer only provides a bound on a respondent's WTP, and more TIOLI respondents than BDM respondents are required to achieve a given precision in estimates of market demand functions.

Together, these considerations motivate the direct comparison of BDM and TIOLI implementations. We proceed with this comparison for four products separately: one insurance policy in 2010, one insurance policy in 2011, four insurance policies in 2011, and a subscription to AO. For all products, the population was randomly allocated to either the BDM procedure or a fixed discount off of the market price.[18]

As mentioned in the previous section, households on the marketing lists were visited to explain the product, and pricing was assigned using a scratch card. In some cases (for both WI and AO), the households refused to participate in the BDM exercise (generally because they were uninterested regardless of the price), and, therefore, did not participate in the scratch card exercise. In these cases, households are assigned a WTP of zero.[19]

Fig. 2 shows the distribution of BDM bids for all four products. These histograms reveal a number of interesting stylized facts.

First, for insurance there are very few bids over the stated market price of the policies. For one policy in 2010, 99.4% of the bids were below or equal to the market price of 150. For the other three products in the figure, all bids were below or equal to the market-level premium. This behavior is expected, as the outcome of the BDM procedure does not vary as bids rise above the maximum of the distribution, and also participants were told that they could purchase the product for market price from other agents (though in practice this would have likely incurred high transaction costs). For AO, a set market price did not exist as the product was not commercially available. However, 18% of respondents bid above the estimated "break-even" cost of providing the product (which was not disclosed to the respondents).

Next, in the insurance case (where respondents could report any integer bid), the bids are concentrated at focal points of round numbers, typically those ending in "00" or "50." For instance, for one policy in 2010, 39% of the respondents expressed WTP of "100." This pattern is consistent across all insurance elicitations and reflects results in previous literature (Green et al., 1998). In the AO case – where the bid choices were discrete – there is no scope for focal point "massing" to occur.

4.1. Comparisons at individual prices

In order to compare BDM to TIOLI, we first study the percentage of participants who expressed a WTP above a certain fixed price (BDM) to the percentage of participants who purchased it when assigned the same fixed price (TIOLI). For instance, when considering a TIOLI offer of Rs. 100, we compare the percentage of people assigned BDM who expressed a WTP greater than or equal to 100 to the percentage of people assigned TIOLI who purchased the insurance. Given a large sample size, these two percentages should be equal if BDM and TIOLI produce equal measures of WTP.

Descriptive comparisons are presented in Table 3. For insurance, the two methods give relatively similar estimates of demand for many price points, though there are significant deviations. For one insurance policy in 2010, 43.6% of participants purchased insurance when offered a fixed price of Rs. 100, and 47.0% of BDM participants expressed a WTP greater or equal to 100, for a difference of only 3.4%. However, there was a difference in estimated demand of over 22% for the TIOLI price of 130. For AO, there is a difference in demand of 12.8% at a price of Rs. 40, but smaller differences for the other prices. There is no consistent direction of bias between BDM and TIOLI; at some points, BDM estimates a higher demand than TIOLI, and in other places, a lower demand. This is in contrast to Berry et al. (2019), who found that BDM consistently measures lower demand than TIOLI.

In 2011, we offered TIOLI prices of Rs. 149 and Rs. 150 for insurance in order to understand whether there was an increase in demand when a price is just below a round number.[20] Demand at the two prices is quite similar (23.0% at Rs. 149 vs. 26.1% at Rs. 150, a difference which is not statistically significant), with demand even nominally higher for the higher price. In the analysis that follows we will pool the TIOLI offers of Rs. 149 and Rs. 150.

[18] For WI, we do not have household-level data on this population to test the effectiveness of our randomization. However, we can test whether the rate of refusal to fill out the scratch cards is the same for the different treatment arms. Within-year this is generally true, but there is one outlier (for BDM1 policy in 2011) that had a statistically significant difference in refusal rates relative to several of the other 2011 arms. This information is presented in Appendix Table A.7.

[19] We provide robustness checks dropping refusals in Appendix Table A.6.

[20] Prices ending in "9" are over-represented in the private sector (Schindler and Kirby, 1997).

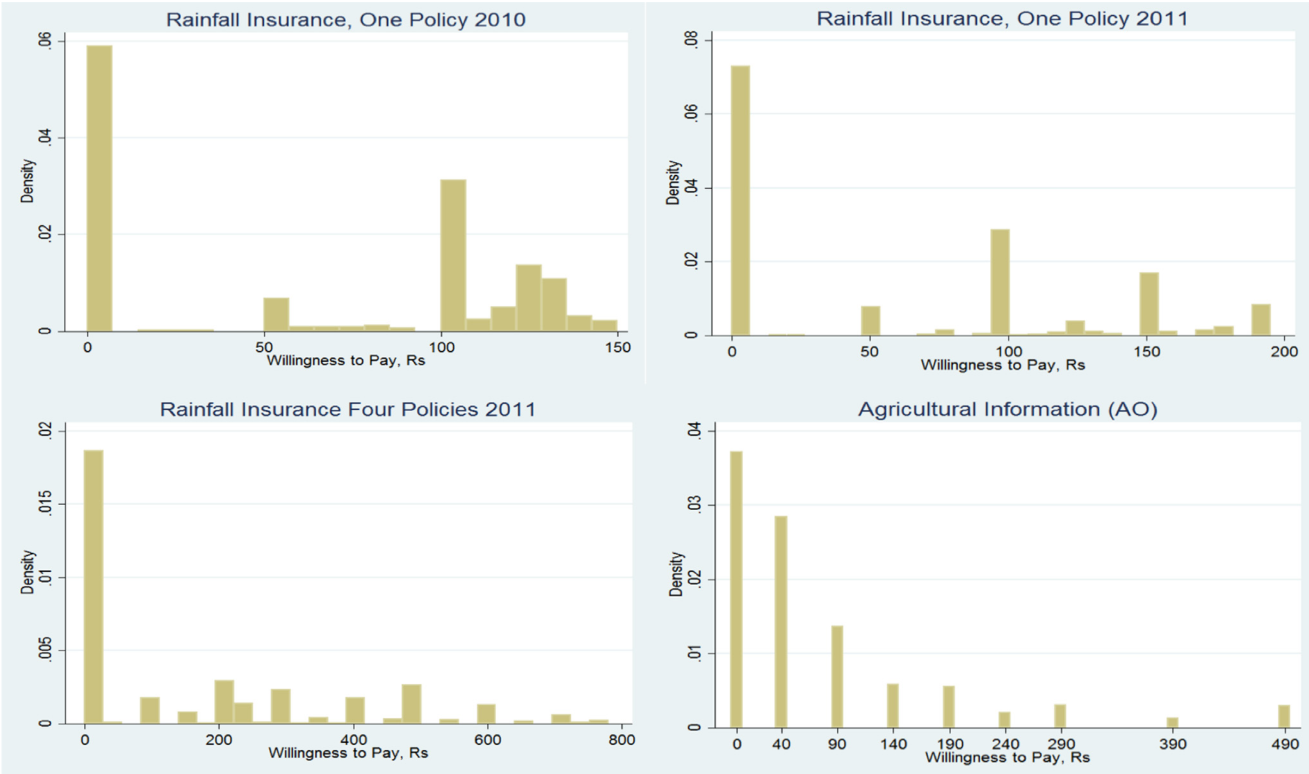

Fig. 2. Distribution of WTP for rainfall insurance and agricultural information elicited by BDM Exercise. *Notes:* This figure shows a histogram for the willingness-to-pay (WTP) for all participants of BDM. WTP is coded as zero if respondents declined to participate.

Table 3
Comparison of BDM and TIOLI at fixed points.

	Price (Rs)	BDM WTP ≥ Price	Bought with TIOLI	Diff
Rainfall Insurance, 2010, 1 Policy (List Premium = 150)	130	11.2%	33.2%	−22.0%
	100	47.0%	43.6%	3.4%
Rainfall Insurance, 2011, 1 Policy (List Premium = 195)	150	17.1%	26.1%	−9.0%
	149	17.1%	23.0%	−5.9%
	99	36.5%	28.9%	7.6%
Rainfall Insurance, 2011, 4 Policies (List Premium = 780)	599	5.9%	3.6%	2.3%
	499	11.8%	6.2%	5.6%
Agricultural Information Service (AO)	40	62.8%	50.0%	12.8%
	90	34.4%	30.6%	3.8%
	140	20.7%	24.6%	−3.9%
	190	14.9%	10.5%	4.4%
	240	9.3%	7.1%	2.2%

Notes: This table compares BDM and TIOLI by reporting actual demand at the TIOLI fixed prices to estimated demand using BDM. For each fixed price, the percentage of people who bought at this price is compared to the percentage of people who expressed a WTP greater than or equal to this fixed price.

Table 4
BDM versus TIOLI.

Panel A: Weather Insurance								
	One Insurance Policy					Bundle of 4 Insurance Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130	Rs 100	Rs 149	Rs 99		Rs 599	Rs 499	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDM Exercise	−0.225***	0.019	−0.072*	0.046	−0.057***	0.019	0.087***	0.065***
	(0.032)	(0.038)	(0.037)	(0.041)	(0.021)	(0.018)	(0.027)	(0.024)
R^2	0.194	0.154	0.196	0.198	0.114	0.213	0.259	0.218
N	1085	1066	895	607	2782	599	595	873

Panel B: Agricultural Information Service (AO)							*Panel C: WI and AO Pooled*
	One Subscription						
	Rs 40	Rs 90	Rs 140	Rs 190	Rs 240	Pooled	All Products Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(1)
BDM Exercise	0.137*	0.051	−0.012	0.059	0.026	0.033	0.033
	(0.079)	(0.065)	(0.055)	(0.041)	(0.033)	(0.033)	(0.032)
R^2	0.066	0.058	0.076	0.076	0.062	0.142	0.127
N	811	815	814	810	809	1047	4702

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. The product being purchased in Panel A is always one insurance policy while the product in Panel B is a 9-month subscription to the AO service. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

We begin our statistical analysis with a simple regression framework, comparing BDM to TIOLI. Specifically, we first test whether the cumulative distribution function of WTP is equal when estimated by BDM versus TIOLI, when evaluated at the TIOLI fixed prices. The regression equation is specified as

$$WTP_{\geq p_i} = \alpha + \beta_1 BDM_i + \beta v_i + \epsilon_i$$

The dependent variable $WTP_{\geq p_i}$ is a dummy that takes the value of 1 if participant i, offered TIOLI at price p, purchased the product, or if that participant, offered BDM, expressed a WTP greater than or equal to p. The independent variable BDM_i is a dummy for whether or not participant i was offered BDM, v_i a vector of village fixed effects, and ϵ_i is an idiosyncratic error term.

The results from this regression for a range of prices p, are given in Table 4 and parallel the intuition given in the previous descriptive analysis. For rainfall insurance, while there are some differences in demand between BDM and TIOLI (particularly at a price of Rs. 130), the sign of the difference is not systematically positive or negative. For one policy, BDM gives generally lower measures of demand, and for 4 policies, it gives generally higher. In the AO experiment, the only marginally statistically significant difference is at the Rs. 40 price point. For AO, the majority of the demand estimated by BDM is higher than the TIOLI estimate, although these are rarely statistically different.

To improve the power of these tests, we also compute a pooled estimate of all the price points. For this specification, each BDM observation is randomly assigned (with equal probability) to be a comparator for one of the associated fixed

Table 5
Price elasticities using BDM and TIOLI.

Price Range	Product	BDM			TIOLI		
		Elasticity	Max	Min	Elasticity	Max	Min
100–130	WI - 1 policy (2010)	−4.716	−3.914	−5.476	−1.038	−0.226	−1.848
99–149	WI - 1 policy (2011)	−1.795	−0.972	−2.585	−0.404	0.445	−1.196
499–599	WI - 4 policies	−3.660	0.136	−7.068	−2.913	2.939	−8.021
40–90	AO	−0.760	−0.577	−0.942	−0.626	0.162	−1.387
90–140	AO	−1.144	−0.625	−1.654	−0.500	1.373	−2.329
140–190	AO	−1.075	−0.068	−2.063	−2.651	0.955	−5.716
190–240	AO	−1.990	−0.356	−3.562	−1.661	5.929	−8.259
40–240	AO	−1.030	−0.681	−1.378	−1.054	−0.436	−1.673

Notes: The arc elasticities for weather insurance and AO are estimated using the BDM and TIOLI demand estimates. The elasticity bounds are computed using the 95% confidence intervals for BDM and TIOLI demand. The price range of 100–130 for weather insurance corresponds to the year 2010, and the price ranges of 99–149 and 499–599 for weather insurance correspond to the year 2011. All the AO price ranges correspond to the year 2011. The TIOLI elasticities for the price range of 99–149 for weather insurance use the average value of TIOLI demand across prices of 149 and 150 for the estimated TIOLI demand at a price of 149. The AO elasticities for the 40–240 range assume an isoelastic demand function.

prices for the product offered in order to calculate the dependent variable $WTP_{\geq p_i}$. In this pooled specification, we find that estimated demand using the BDM procedure for 1 weather insurance policy is lower than TIOLI by approximately 5.7 percentage points. This negative coefficient is driven by the fact that the BDM procedure resulted in much lower demand when compared to the TIOLI price of Rs. 130. For four policies, the pooled specification shows that BDM produces estimates of demand that are 6.5 percentage points higher than those produced by TIOLI.

For AO, the point estimate from the pooled specification is positive but not significant. While this estimate isn't a 'tight zero', we view these results as suggesting that BDM does not introduce a systematic bias and certainly does not underestimate demand as suggested elsewhere in the literature. Second, the AO results provide suggestive evidence that the discrete price point method of BDM used in AO may result in demand that more closely aligns with TIOLI.

Finally, Panel C of Table 4 presents the results of a specification pooling data across all of the products. This point estimate implies that BDM reduces the probability of purchasing by a statistically insignificant 3.3 percentage points with a standard error of 3.2 percentage points, a tightly estimated null effect.[21]

4.2. Comparisons of estimated elasticities

In Table 5, we report arc price elasticities of demand implied by the demand elicited for both products. To compare elasticities, we use the BDM bids to compute demand at identical price points to the TIOLI offers. For the AO product, we find that the estimated elasticities are fairly comparable by method for the lowest and the highest ranges. However, in the intermediate Rs. 140–190 range, TIOLI implies an elasticity twice as large as BDM while the reverse is true for the Rs. 90–140 range. However, in all cases, the estimated elasticities fall within the 95% confidence intervals of their comparison method. Moreover, if we assume an isoelastic demand function across the Rs.40–240 range, we find the point estimates for the estimated elastictity for BDM and TIOLI are virtually indistinguishable.

As suggested by the point-wise comparisons above, the story for weather insurance is different. The estimated price elasticities of demand are very different for the Rs. 100–130 range by method. While BDM implies an elasticity of -4.716, TIOLI estimates it at -1.038. Were we to compute the most elastic and inelastic curves implied by these confidence intervals, there would be no overlap for this specific range. This is, however, the exception among the estimated elasticities and we find that, overall, both methods of demand elicitation deliver comparable elasticities across a broad range of prices and products.

4.3. Comparisons of distributions

While the prior analysis compares demand elicited by BDM and TIOLI at specific points along the demand curve and elasticities across specific price ranges, we now turn to a related question: do the two procedures yield statistically different demand curves?

Variation in TIOLI prices allows us to trace out a partial demand curve (had we had a larger sample and varied the TIOLI prices continuously, we would have obtained a complete demand curve). For instance, if 33% of respondents purchased at a TIOLI price of Rs. 130, and 40% at a TIOLI price of Rs. 100, and (as we assume) demand is weakly decreasing in price, then the demand curve at prices between Rs. 100 and Rs. 130 must lie between 33% and 40%, though our data do not allow us to say whether 33.1% or 39.9% would purchase at a price of Rs. 101. We also establish a point on the demand curve at a price

[21] Appendix Tables A.4–A.6 probe the robustness of these results to various treatment of non-compliant bids. Specifically, we treat their WTP as valid in Appendix Table A.4, as providing bounds for their actual WTP in Appendix Table A.5 and excluding them in Appendix Table A.6.

Table 6
Tests of Equality of Distributions between BDM and TIOLI Demand Curves

	Rainfall Insurance			AO
	1 Policy 2010	1 Policy 2011	4 Policies 2011	(Chi-Squared Test)
K-S D Statistic	0.215	0.079	0.056	3.056
P-Value	0.000	0.030	0.259	0.585

Notes: This table presents a test of whether the WTP distribution observed from the BDM game could have been drawn from an underlying WTP distribution that is within the bounds set by particpants' TIOLI choices. In the case of AO, we used a Chi-squared test (Press et al., 1992). For the remaining comparisons, we use the K-S D statistic to test for the maximum difference between the cumulative distribution of WTP as calculated by BDM and the WTP distribution with the bounds of TIOLI that is closest to the BDM distribution. The *P*-value is calculated using Gleser's (1985) application of the K-S test to discrete distributions.

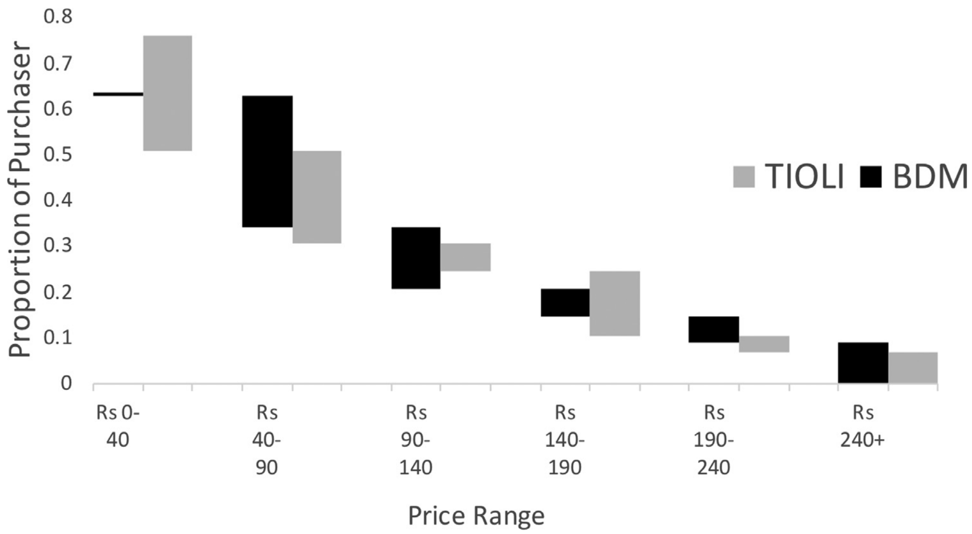

Fig. 3. Demand curve overlap for BDM and TIOLI for Agicultural Information (AO). *Notes:* This figure shows the bounded demand curve for AO derived from TIOLI and BDM choices. There is overlap in the bounds throughout the distribution.

of zero, defined as the percentage of participants that accepted the marketing call and therefore participated in the scratch card exercise.[22]

In order to compare the distributions for AO produced by BDM and TIOLI, we use the chi-square test (Press et al., 1992). In Table 6, we find that the distributions produce a chi-squared value of 3.056 (p-value = 0.585) suggesting that we cannot reject equality of distributions in this case. This is suggested by Fig. 3, as the bounds of the demand curve suggested by BDM and TIOLI are always overlapping.

For WI, as exact WTP was elicited with BDM, we can draw an exact demand curve. In this case, there are some price ranges for which the BDM demand curve lies outside the bounds of the TIOLI demand curve. In Fig. 4, we plot the demand curve estimated using BDM and the point estimates demand curve bounds defined by TIOLI. For four policies in 2011, the WTP curve estimated by BDM falls mostly within the TIOLI bounds. For both one-policy elicitations, BDM delivers similar demand estimates at prices near Rs. 100, but underestimates demand for the higher price point relative to TIOLI.

In Table 6 we report the results of a Kolmogorov-Smirnov (K-S) test of the equality of distributions between the demand curve estimated using BDM and the demand curve within the bounds defined by TIOLI that is closest to the BDM demand curve. Because we are comparing two discrete distributions, the K-S D-statistic is simply the maximum absolute difference of the cumulative distribution function of these two distributions. We derive the p-values of the K-S D-statistic for the discrete case using the technique outlined in Gleser (1985).

For one insurance policy in 2010, the equality of distributions is rejected, driven by differences in demand at a price of Rs. 130. For one insurance policy in 2011, equality of the distributions is also rejected, with a p-value of 0.03. However, for four policies in 2011, we are unable to reject the null hypothesis of equality of distributions (p=0.259). These results suggest there are some meaningful differences in the distributions elicited by TIOLI and BDM, consistent with the fixed point comparisons.[23]

Overall, we find results that differ for the different products and elicitation methods, highlighting that BDM may perform differently in different circumstances. Exactly what is driving these differences is not completely identified, but we can make

[22] If people were not willing to engage marketing staff or participate in the BDM exercises, we assume they have no demand for the product at any price.
[23] Pooling all demand elicitations for weather insurance and using a chi-squared test again allows us to reject equality of distributions.

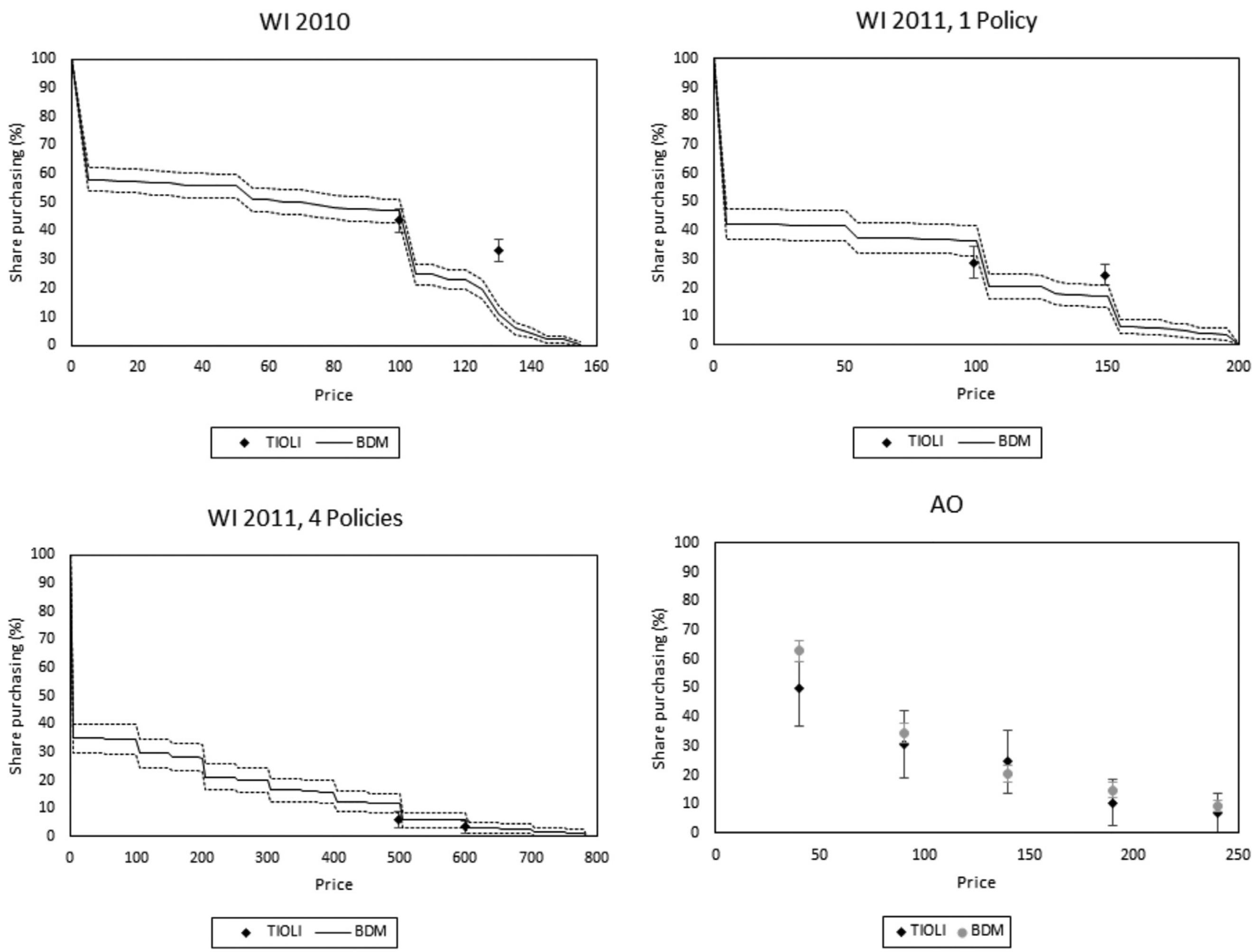

Fig. 4. Demand curves implied by BDM and TIOLI. *Notes:* The panels of this figure compare demand curves implied by TIOLI and BDM. In each panel, the horizontal axis is the price and the vertical axis is the fraction of respondents who purchased. The point at a price of zero equals 1 minus the proportion of people who refused to receive marketing. In each case, we plot the TIOLI point estimates and the 95% confidence interval. In the case of BDM, we plot the demand curve and the 95% confidence intervals except in the case of AO (panel D) where a discrete form of BDM was used.

some hypotheses. For weather insurance, it is worth noting BDM appears to underestimate WTP for an inexpensive product (1 policy), but overestimates WTP for a more expensive product (4 policies). It is an interesting question for future research whether this is a general trend. We believe it is likely that the strong alignment between TIOLI for AO is driven by the usage of the reframed BDM method in which participants choose their WTP from a list of discrete price points. The strong performance of this reformulation of the BDM method is consistent with a lab implementation of a similar mechanism in de Meza and Reyniers (2013).

5. Effect heterogeneity

5.1. Treatment exposure

In Appendix Table A.8, A.9 and A.10 we use exogenous variation in the treatment status of respondents – and, in the case of weather insurance, realized payouts – to understand whether differential levels of exposure to the treatment may influence demand and how this is captured by the two elicitation methods. In Appendix Table A.8, in the case of WI, we observe that while one's treatment status is correlated with higher bids, there is no systematic relationship between having had weather insurance (or received payouts) in the past and the difference in WTP as elicited by BDM versus TIOLI. As a corollary, we see in Appendix Table A.11 that this follows for estimated arc elasticities. In particular, the estimated arc elasticities are similar for both those who had bought insurance previously and those who had not.

We see a similar story in the case of AO, where respondents assigned to the treatment group do not systematically change their bids for BDM relative to those in control. In the case of AO, those in treatment do not have a higher demand on average, which is perhaps accounted for by spillover effects in an information product. Similarly, in Appendix Table A.11, the estimated arc elasticties do not differ systematically by treatment status or by the method through which they are elicited.

We also examine whether demand estimates for AO systematically vary by a proxy for risk preferences – as in Berry et al. (2019) – in Appendix Table A.12 but do not find evidence to suggest this is the case.

6. Recommendations for demand elicitation in the field

Overall, we do not find systematic differences in estimated demand and arc price elasticities computed by BDM and TIOLI for the same product. While the case of rainfall insurance appears more volatile with large differences in estimated demand and elasticities for the 1 policy in 2010, rarely is estimated demand statistically distinguishable. As Fig. 4 shows, BDM, by virtue of the increased information provided, confers an efficiency advantage in terms of the precision and amount of information gleaned from each respondent but may be susceptible to the issue of focal points among other bidding behaviors that do not follow from standard expected utility maximization.

Our recommendation for future field work, particularly in low literacy environments such as our two field sites in India, would be to design a modified version of the BDM game that uses a series of discrete price intervals as in the mechanism used for AO. These mechanisms are similar to the 'reframed' BDM (or rBDM) games proposed and used by Loewenstein and Adler (1995) and de Meza and Reyniers (2013). Our findings suggest that the rBDM procedure produces elasticities and demand estimates that cannot be distinguished from those given by TIOLI.

We see a number of potential advantages in using this mechanism: first, discrete choices mimic real-world situations relative to a BDM game with continuous bidding, reducing confusion about how the mechanism operates. Second, it reduces the salience of the lottery aspect of BDM which may play a role in non-EU bidding strategies. Third, as we show, this method mechanically reduces the influence of focal points.

Of course, the rBDM mechanism will glean less information than standard BDM, but we observe from the confidence intervals in the AO panel for Fig. 4, that there is still a substantial efficiency gain relative to TIOLI. Second, when considering the cost of training enumerators, staff required to successful implement BDM, and the fixed costs involved in traveling to remote villages to market AO, we find that the cost per person for rBDM is $3.04, relative to $1.69 for TIOLI and $5.46 for BDM.[24]

While both the fixed and variable costs of the two mechanisms will vary greatly by context, according to the density of households in the study area and the number of price points over which respondents are asked to make choices. Overall, our results suggest that the additional cost of rBDM may well be justified as it produces results that are comparable to TIOLI and has substantial benefits in deriving precise estimates of demand as suggested by the simulation framework in Section 2.

7. Conclusion

This paper assesses the performance of a Becker-DeGroot-Marschak incentive compatible preference elicitation mechanism when implemented at a large scale in the field. We find that in many cases BDM yields measures of demand that are

[24] This cost structure was established in consultation with our field survey teams and is reported in detail in Appendix A.13. Of course, the precise costs will vary by the structure of the survey teams and the methods through which BDM is implemented. In our case this required scratch cards and a call operator to accurately reveal offers and record bids.

comparable to take-it-or-leave-it offers, though with notable exceptions. We do not find evidence of a systematic directional bias, and find low rates of non-compliance.

We find the BDM modestly underestimated demand for one insurance policy, modestly overestimates demand for four insurance policies, and lines up well with TIOLI for the AO case. These findings suggest that the performance of BDM likely depends on the context: both the price of the product and the specific elicitation method plausibly affect BDM's performance.

Together, these empirical results provide support for the view that there is no systematic bias in estimated demand between BDM and TIOLI. In addition BDM confers significant advantages: a simple simulation framework shows that the benefits of BDM can be large, especially when experimental sample sizes are small. Where experimenters have reason to believe that estimates maybe influenced by focal points, they may prefer to use BDM with a set of discrete price points.

Our results connect with other methodological work and with diverse implementations of incentive-compatible elicitation. The paper also suggests a number of avenues for future research. First, it provides suggestive evidence that BDM may underestimate demand for products with low prices, and overestimate demand for products with high prices. It would be interesting to see if this is replicated in other contexts. Next, it suggests that a modified elicitation method for BDM (rBDM) used in the AO case may give more reliable estimates of demand.

Overall, we conclude that BDM can be successfully implemented in the field, producing estimates of consumer demand that are both reliable and useful. While BDM is not perfect, we believe that with careful implementation it can be an important part of a field experimenter's toolkit when exploring markets for new products in developing countries.

Declaration of Competing Interest

1. This research received support from the USAID-BASIS, Agricultural Technology Adoption Initiative, AusAid and Sustainability Science Program at the Harvard Kennedy School.
2. Apart from these grants, we have not received any financial support from any interested party.
3. Appropriate institutional review board authorization was obtained from Harvard University to link and analyze data.
4. Fernando is an (unpaid) Research Affiliate of Precision Agriculture for Development (PAD). PAD Is a not-for-profit organization that is dedicated to scaling mobile phone-based agricultural extension.
5. Cole is on the board (unpaid) for Precision Agriculture for Development (PAD). PAD Is a not-for-profit organization that is dedicated to scaling mobile phone-based agricultural extension.

Appendix A

Table A.1
Sample Termsheet 2010.

Agriculture Insurance Company of India Ltd.

WEATHER BASED CROP INSURANCE SCHEME (KHARIF 2010)

TERM SHEET

State **GUJ** Distrcit: **Ahmadabad** Tehsil: **Barvala**

Crop: **Generic Crop**	Reference Weather Station: **Barvala**		**Unit: PER ACRE**

1. DEFICIT RAINFALL

		PHASE - I	PHASE - II	PHASE - III
1 A. RAINFALL VOLUME	PERIOD	16-Jun to 15-Jul	16-Jul to 20-Aug	21-Aug to 30-Sep
	TRIGGER I (<)	100 mm	150 mm	70 mm
	TRIGGER II (<)	50 mm	75 mm	30 mm
	EXIT	0	0	0
	RATE I (Rs./ mm)	1.25	1.00	1.25
	RATE II (Rs./ mm)	7.50	4.83	6.67
	Max. Payout (Rs.)	437.50	437.50	250

TOTAL PAYOUT (Rs.)	1125

2.

		PHASE - I	PHASE - II
EXCESS RAINFALL (Multiple events)	PERIOD	1-Sep to 20-Sep	21-Sep to 10-Oct
	DAILY RAINFALL TRIGGER (>)	80 mm	50 mm
	EXIT (mm)	160 mm	120 mm
	Payout (Rs. / mm)	1.56	3.57
	Max. Payout	125	250

TOTAL PAYOUT (Rs.)	375

TOTAL SUM INSURED (Rs.)	1500
PREMIUM with S Tax (Rs.)	150
PREMIUM %	10.00%

Table A.2
Sample Termsheet 2011.

Agriculture Insurance Company of India Ltd.

WEATHER BASED CROP INSURANCE SCHEME (KHARIF 2011)

TERM SHEET

State **GUJ** Distrcit: Ahmadabad Block: DHANDHUKA

Crop:	Generic Crop	Reference Weather Station:	DHANDHUKA	Unit:	PER HECTARE

1. DEFICIT RAINFALL

1 A. RAINFALL VOLUME

	PHASE - I	PHASE - II	PHASE - III
PERIOD	16-Jun to 15-Jul	16-Jul to 20-Aug	21-Aug to 30-Sep
TRIGGER I (<)	80 mm	100 mm	50 mm
TRIGGER II (<)	40 mm	50 mm	15 mm
EXIT	0	0	0
RATE I (Rs./ mm)	2.5	1.50	2
RATE II (Rs./ mm)	8.44	7.25	12.00
Max. Payout (Rs.)	437.50	437.50	250

TOTAL PAYOUT (Rs.)	1125

Note: In case of Deficit cover Daily maximum rainfall was capped at 60 mm and if the rainfall in a day is less than or equal to 2 mm, then that will be not be counted in rainfall volume under this cover.

2. EXCESS RAINFALL COVER:
Cover Definition: Sum of 2 Consecutive days' rainfall (mm).

EXCESS RAINFALL COVER (Single maximum event for each phases will be paid)

	PHASE - I	PHASE - II	PHASE - III
PERIOD	16-Jun to 20-Jul	21-Jul to 20-Sep	21-Sep to 31-Oct
RAINFALL TRIGGER (>)	250 mm	225 mm	60 mm
EXIT (mm)	350 mm	325 mm	150 mm
Payout (Rs. / mm)	1.25	2.50	2.78
Max. Payout	125	250	250

TOTAL PAYOUT (Rs.)	625

TOTAL SUM INSURED (Rs.)	1750
PREMIUM with S Tax (Rs.)	195
PREMIUM %	11.14%

Note: Franchise of Rs50 shall be apllicable, i.e., total claims of less than Rs50 shall not be paid.

Table A.3
Correlates of non-compliance.

	(1) WI 1 Policy	(2) WI 4 Policies	(3) AO	(4) AO
BDM Offer	0.00133**	0.00045	0.00234***	0.00241***
	(0.00047)	(0.00023)	(0.00043)	(0.00044)
Can Read and Write				−0.10969
				(0.08850)
Age				−0.00072
				(0.00267)
Years of Education				0.00382
				(0.01119)
Constant	−0.00535	0.05137	−0.04419	0.03577
	(0.02190)	(0.03694)	(0.04465)	(0.11240)
N	427	267	261	261

Notes: Dependent variable is a dummy that takes a value of 1 if the participant is non-compliant, meaning they were supposed to purchase the product but did not. Sample is all participants who were assigned the BDM game and whose offer price was lower than their bid. Standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Appendix Table A.4

There are a number of robustness checks to these results that particularly try to assess the robustness of these results with respect to non-compliant bids. Appendix Table A.4 includes all participants who made non-compliant BDM bids, and treats their provided WTP as valid.

The results in Appendix Table A.4 are generally consistent with the main findings. However, the pooled AO coefficient becomes positive and marginally significant, suggesting that BDM may elicit higher WTP than TIOLI in the AO case.

Table A.4
BDM versus TIOLI, including non-compliants.

Panel A: Weather Insurance								
	One Insurance Policy					Bundle of 4 Insurnace Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130	Rs 100	Rs 149	Rs 99		Rs 599	Rs 499	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDM Exercise	−0.231***	0.006	−0.077**	0.040	−0.068***	0.018	0.082***	0.062**
	(0.031)	(0.037)	(0.037)	(0.041)	(0.021)	(0.018)	(0.026)	(0.024)
R^2	0.192	0.146	0.194	0.194	0.110	0.213	0.255	0.217
N	1107	1088	904	616	2813	610	606	884

Panel B: Agricultural Information Service (AO)							*Panel C: WI and AO Pooled*
	One Subscription						
	Rs 40	Rs 90	Rs 140	Rs 190	Rs 240	Pooled	All Products Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(1)
BDM Exercise	0.157*	0.086	0.031	0.088**	0.061*	0.059*	0.059*
	(0.078)	(0.064)	(0.056)	(0.040)	(0.033)	(0.032)	(0.032)
R^2	0.062	0.063	0.080	0.090	0.068	0.145	0.123
N	863	867	866	862	861	1099	4796

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. The product being purchased in Panel A is always one insurance policy while the product in Panel B is a 9-month subscription to the AO service. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Appendix Table A.5

Appendix Table A.5 includes participants who made non-compliant bids, but considers their WTP as bounded by their actual purchase choice. For instance, consider a situation where someone received an offer of 100, it was less than their bid, and then they declined to purchase. In this case, we consider their WTP as being bounded above by 100. Therefore, for comparisons to TIOLI prices greater than 100, we can count them as a non-purchaser. For TIOLI prices below 100, their decision is undefined and they are left out of this regression. The results in Appendix Table 5 are generally consistent with

Table A.5
BDM versus TIOLI, including non-compliants, PART B sepecification.

Panel A: Weather Insurance								
	One Insurance Policy					Bundle of 4 Insurnace Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130	Rs 100	Rs 149	Rs 99		Rs 599	Rs 499	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDM Exercise	−0.222***	0.009	−0.071*	0.045	−0.062***	0.018	0.082***	0.062**
	(0.031)	(0.037)	(0.036)	(0.041)	(0.020)	(0.018)	(0.026)	(0.024)
R^2	0.186	0.148	0.194	0.199	0.110	0.213	0.255	0.217
N	1107	1085	904	613	2813	610	606	884

Panel B: Agricultural Information Service (AO)							*Panel C: WI and AO Pooled*
	One Subscription						
	Rs 40	Rs 90	Rs 140	Rs 190	Rs 240	Pooled	All Products Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(1)
BDM Exercise	0.157*	0.086	0.031	0.088**	0.061*	0.059*	0.059*
	(0.078)	(0.064)	(0.056)	(0.040)	(0.033)	(0.032)	(0.032)
R^2	0.062	0.063	0.080	0.090	0.068	0.145	0.123
N	863	867	866	862	861	1099	4796

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooleds specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. The product being purchased in Panel A is always one insurance policy while the product in Panel B is a 9-month subscription to the AO service. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

the main findings. However, in both of these tables the pooled AO coefficient becomes positive and marginally significant, suggesting that BDM may elicit higher WTP than TIOLI in the AO case.

Appendix Table A.6

Table 6 in the appendix removes respondents who refused to participate (and are therefore coded as a WTP of zero for both BDM and TIOLI in the main specification) Here the pattern of estimates is similar to that in the main specification, but the differences between BDM and TIOLI are magnified. This is expected mechanically, as by construction the dropped observations align between BDM and TIOLI. In this specification, again the pooled AO coefficient becomes positive and marginally significant.

Table A.6
BDM versus TIOLI, excluding those who declined participation.

Panel A: Weather Insurance

	One Insurance Policy					Bundle of 4 Insurnace Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130 (1)	Rs 100 (2)	Rs 149 (3)	Rs 99 (4)	(5)	Rs 599 (6)	Rs 499 (7)	(8)
BDM Exercise	−0.398***	0.072	−0.289***	0.065	−0.144***	0.040	0.193**	0.145**
	(0.065)	(0.044)	(0.083)	(0.068)	(0.037)	(0.052)	(0.074)	(0.063)
R^2	0.290	0.247	0.380	0.373	0.200	0.386	0.459	0.369
N	618	631	358	244	1405	212	229	329

Panel B: Agricultural Information Service (AO) / *Panel C: WI and AO Pooled*

	One Subscription						Panel C
	Rs 40 (1)	Rs 90 (2)	Rs 140 (3)	Rs 190 (4)	Rs 240 (5)	Pooled (6)	All Products Pooled (1)
BDM Exercise	0.196**	0.081	0.015	0.078*	0.033	0.060*	0.060*
	(0.080)	(0.069)	(0.058)	(0.041)	(0.033)	(0.034)	(0.034)
R^2	0.079	0.071	0.092	0.095	0.068	0.159	0.333
N	762	766	765	761	760	998	2732

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The “BDM Exercise” variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. The product being purchased in Panel A is always one insurance policy while the product in Panel B is a 9-month subscription to the AO service. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.7
Balance of BDM vs TIOLI randomization.

	BDM		1 Policy TIOLI Price				
2010	1 Policy	4 Policies	Rs 130	Rs 100			
Percentage Refusing Scratch Card	40.3%	40.5%	43.0%	38.5%			
Standard Error	0.021	0.022	0.021	0.021			
N	556	494	551	532			
	BDM		4 Policies TIOLI Fixed Price		1 Policy Fixed Price		
2011	1 Policy	4 Policies	Rs 599	Rs 499	Rs 150	Rs 149	Rs 99
Percentage Refusing Scratch Card	55.8%	61.4%	64.0%	57.3%	58.2%	64.4%	62.2%
Standard Error	0.027	0.027	0.029	0.030	0.029	0.029	0.030
N	346	332	278	274	280	278	270

Notes: This table lists the percentage of people refusing to participate in the scratch card exercise for the different treatment arms. Households are marked as refusing if they were assigned a scratch card and visited during marketing, but the household refused to scratch the card. Most within-year differences are not statistically significant. The one exception is the refusal rate in 2011 for BDM 1 policy, which is lower than the other treatment arms. It is statistically different at the 5% level from the refusal rate of TIOLI fixed prices of Rs. 699 and 149.

Table A.8
BDM versus TIOLI, had weather insurance in the past.

Panel: Weather Insurance								
	One Insurance Policy					Bundle of 4 Insurnace Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130	Rs 100	Rs 149	Rs 99		Rs 599	Rs 499	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDM Exercise	−0.220***	0.023	−0.078*	0.037	−0.056**	0.028	0.059**	0.048**
	(0.034)	(0.044)	(0.040)	(0.051)	(0.023)	(0.020)	(0.029)	(0.022)
BDM × Had WI	−0.025	−0.031	−0.015	−0.015	−0.027	−0.023	0.041	0.021
	(0.092)	(0.074)	(0.054)	(0.078)	(0.048)	(0.040)	(0.042)	(0.043)
Had WI	0.050	0.120*	0.166***	0.309***	0.093**	0.050*	0.039	0.048*
	(0.077)	(0.060)	(0.042)	(0.053)	(0.037)	(0.028)	(0.030)	(0.024)
R^2	0.195	0.161	0.229	0.282	0.119	0.220	0.269	0.229
N	1085	1066	895	607	2782	599	595	873

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.9
BDM versus TIOLI, had weather insurance payout in the past.

Panel: Weather Insurance								
	One Insurance Policy					Bundle of 4 Insurnace Policies		
	2010		2011		Pooled	2011		Pooled
	Rs 130	Rs 100	Rs 149	Rs 99		Rs 599	Rs 499	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDM Exercise	−0.227***	0.023	−0.064*	−0.001	−0.063***	0.013	0.066***	0.040**
	(0.033)	(0.039)	(0.036)	(0.044)	(0.022)	(0.016)	(0.022)	(0.016)
BDM × Had WI	0.009	−0.393**	−0.135*	0.066	−0.078	0.005	0.035	0.044
	(0.228)	(0.160)	(0.078)	(0.085)	(0.087)	(0.056)	(0.059)	(0.060)
Had WI	0.133	0.626***	0.303***	0.238***	0.193***	0.043	0.077*	0.075*
	(0.258)	(0.095)	(0.056)	(0.069)	(0.056)	(0.044)	(0.045)	(0.042)
R^2	0.195	0.166	0.254	0.253	0.116	0.220	0.277	0.240
N	1085	1066	895	607	2782	599	595	873

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.10
BDM versus TIOLI, had agricultural information service in the past.

Panel: Agricultural Information Service (AO)						
	One Subscription					
	Rs 40	Rs 90	Rs 140	Rs 190	Rs 240	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
BDM Exercise	0.165	−0.073	−0.031	−0.034	0.007	−0.003
	(0.124)	(0.114)	(0.090)	(0.081)	(0.054)	(0.054)
BDM × Had AO	−0.034	0.182	0.027	0.137	0.029	0.053
	(0.140)	(0.128)	(0.105)	(0.082)	(0.073)	(0.063)
Had AO	0.119	−0.086	0.014	−0.112	−0.001	0.005
	(0.128)	(0.124)	(0.099)	(0.094)	(0.068)	(0.051)
R^2	0.073	0.066	0.078	0.079	0.064	0.145
N	811	815	814	810	809	1047

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.11
Demand elicitation by exposure to treatment.

Price Range	BDM			TIOLI		
	Elasticity	Max	Min	Elasticity	Max	Min
Panel A: Weather Insurance, Previous Insurance Purchase						
100–130	−4.71	−6.59	−2.51	−1.21	−2.78	0.38
99-149	−1.77	−2.93	−0.53	−0.53	−1.39	0.39
499–599	−4.18	−9.04	1.71	−1.95	−7.80	4.45
Panel B: Weather Insurance, No Previous Insurance Purchase						
100–130	−4.73	−5.90	−3.43	−0.98	−1.92	−0.04
99–149	−1.88	−4.05	0.71	0.06	−1.52	1.84
499–599	−2.27	−11.18	8.40	−6.83	−13.85	9.86
Panel C: AO Treatment Group						
40–90	−0.71	−0.50	−0.93	−0.76	0.16	−1.66
90–140	−1.21	−0.61	−1.80	−0.13	2.16	−2.48
140–190	−1.10	0.09	−2.26	−3.67	0.77	−6.82
190–240	−1.85	0.08	−3.71	0.47	9.27	−9.37
Panel D: AO Control Group						
40–90	−0.87	−0.52	−1.23	−0.29	1.26	−1.71
90–140	−0.97	0.07	−1.97	−1.17	2.06	−3.91
140–190	−1.02	0.88	−2.86	−0.72	5.04	−6.79
190–240	−2.28	0.84	−5.15	−4.76	9.28	−11.12

Notes: Panel A reports the arc elasticities for weather insurance based on the BDM and TIOLI demand estimates for those who had previously purchased weather insurance. Panel B reports the arc elasticities for weather insurance based on the BDM and TIOLI demand estimates for those who had not previously purchased weather insurance. Panel C reports the arc elasticities for AO based on the BDM and TIOLI demand estimates for the AO treatment group. Panel D reports the arc elasticities for AO based on the BDM and TIOLI demand estimates for the AO control group. The elasticity bounds are computed using the 95% confidence intervals for BDM and TIOLI demand. The price range of 100–130 for weather insurance corresponds to the year 2010, and the price ranges of 99–149 and 499–599 for weather insurance correspond to the year 2011. All the AO price ranges correspond to the year 2011. The TIOLI elasticities for the price range of 99–149 for weather insurance use the average value of TIOLI demand across prices of 149 and 150 for the estimated TIOLI demand at a price of 149.

Appendix Table A.12

Risk preferences

In Appendix Table A.12, we estimate how demand for an AO subscription varies with risk preferences and the elicitation mechanism.[25] Risk preferences were computed using standard questions about preferences among lotteries that ask a respondent to trade-off increasingly risky choices.[26]

Table A.12
BDM versus TIOLI, risk preference, agricultural information service (AO).

Whether High Risk Seeking or Not (Dummy variable), 0(Risk Averse) or 1(Risk Seeking)						
	One Subscription					
	Rs 40 (1)	Rs 90 (2)	Rs 140 (3)	Rs 190 (4)	Rs 240 (5)	Pooled (6)
BDM Exercise	0.102	−0.070	−0.077	−0.001	0.007	−0.027
	(0.107)	(0.110)	(0.111)	(0.064)	(0.059)	(0.048)
BDM × Risk Seeking	0.093	0.207	0.105	0.122*	0.036	0.113*
	(0.153)	(0.134)	(0.113)	(0.071)	(0.086)	(0.063)
Risk Seeking	−0.036	−0.190	−0.095	−0.123*	−0.034	−0.135**
	(0.144)	(0.122)	(0.117)	(0.069)	(0.081)	(0.057)
R^2	0.071	0.059	0.076	0.078	0.062	0.167
N	803	806	807	803	802	1037

Notes: The dependent variable is an indicator for purchasing insurance (for TIOLI observations) or stating a WTP greater than or equal to the fixed price (for BDM observations). Risk preferences were coded using standard risk lotteries and with a value of 1 signifying an above median risk seeking response (below median risk aversion). The "BDM Exercise" variable is a dummy taking the value of 1 if the observation was from a person who participated in the BDM exercise. In pooled specification, BDM observations are randomly coded to be used as comparison for one of the fixed discounts. All regressions include village fixed effects, and standard errors are clustered at the village level. In the pooled specifications, dummies for each price are also included. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

[25] Risk preferences were not elicited for the WI sample.

[26] Respondents were asked which option they prefer over a series of coin-toss lotteries: Option A: Rs. 25 for heads, Rs. 25 for tails Option B: Rs. 22 for heads, Rs. 47 for tails Option C: Rs. 20 for heads, Rs. 60 for tails Option D: Rs. 17 for heads, Rs. 63 for tails Option E: Rs. 15 for heads, Rs. 75 for tails Option F: Rs. 10 for heads, Rs. 80 for tails Option G: Rs. 5 for heads, Rs. 95 for tails Option H: Rs. 0 for heads, Rs. 100 for tails.

Table A.13
Cost structure of demand elicitation methods.

	TIOLI	BDM	RBDM	Notes/Assumptions
Surveyor Training	$10	$19	$19	Cost:$6.46/day Training days: TIOLI=1.5 days (R)BDM=3 days1 surveyor
Time at Household	15 min/survey 12HH/day 8.33 days	43 min/survey 4HH/day 25 days	30 min/survey 8HH/day 12.5 days	
Call Center/ æBack Upg Operations	$0	$130	$67	Wage: $5.38 wage/day TIOLI=0 surveyor (R)BDM=1 surveyor
Field Operations	$11	$350	$175	Salary: $6.46/day Per diem: $7.53/day Surveyor Travel: $2.15
Scratch Card Cost	$43	$43	$43	Scratch Card Cost:$0.43/card 100 surveys
Total Cost Per 100 HH	$169.32	$546.71	$304.56	
Cost per Person	$1.69	$5.46	$3.04	

Notes: Conversion Rate Used (2011): 1USD = 46.46 INR. This cost exercise assumes 100 Households for each method. Per diem refers to meals and accommodation for the surveyor.

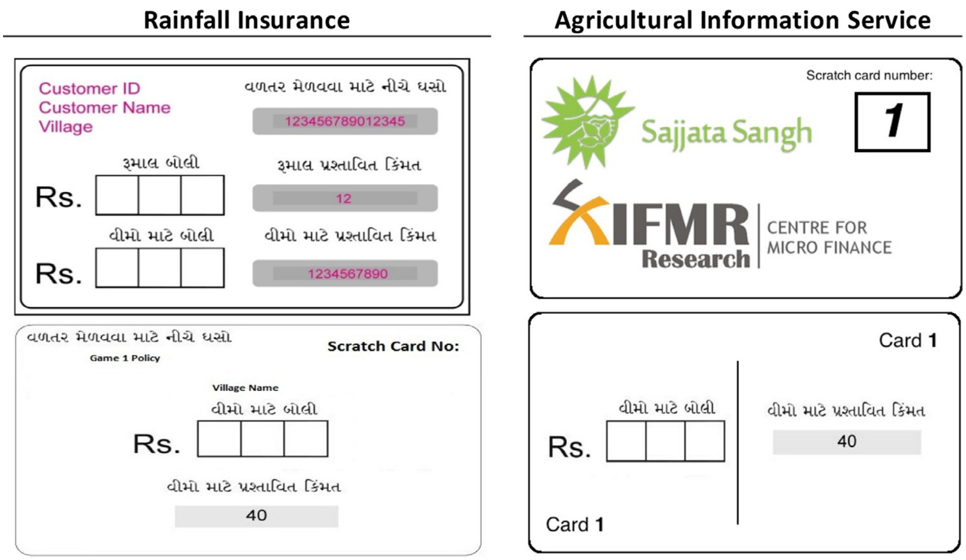

Fig. A.1. Implementation Using Scratch Cards. *Notes:* Panel A shows an example of a scratch card used in 2011 in the weather insurance study. The upper-left corner of the scratch card lists the ID, name, and village of the scratch card holder. To its right is a scratch pane that reveals whether the participant will receive the BDM exercise or a fixed discount. Below this is a field that allows the participant to conduct the BDM exercise for a napkin as a practice. The participant writes her bid in the boxes on the left and then scratches off the offer price on the right. Below this is space to conduct the BDM exercise for the insurance policy. Panel B shows a scratch card used in 2013 for the weather insurance study. It no longer is assigned to a specific customer, and it is only used for BDM (not fixed prices). It is used just for insurance; there is no practice for a napkin. Panels C and D show a scratch card using for the agricultural information service in 2013. Panel C displays the number (1–5) which the phone operator would tell the surveyor the respondent has been assigned to. On the left side, the participant records their bid, while on the right she scratches off the pane to reveal the offer price.

We report results using a binary measure of risk – the results are qualitatively similar, though less precise, using a continuous measure – where 1 codes below median risk aversion (i.e. risk seeking) and 0 codes above median risk aversion. In all specifications, the interaction term between BDM and a dummy for 'Risk Seeking' is positive, suggesting that those who are risk seeking bid more on BDM relative to TIOLI. However, our estimates are only precise in the case of the Rs. 190 offer (col 4) and the pooled specification. It is worth noting that our results are in line with Berry et al. (2019) who find that the BDM-TIOLI gap is largest among the most risk averse subjects in their experiment.

Appendix B. Field procedures and products

This section provides additional detail on the field procedures and products in the two experiments.

B1. Weather insurance policies

The insurance product was developed in coordination with SEWA to fit the needs of their members, and SEWA conducted outreach, marketing, and payout delivery. The product was a rainfall index insurance policy that paid out in the event of deficit or excess rainfall. The Agricultural Insurance Company (AIC) of India underwrote the policies, with terms that varied slightly based on location and year. In general, the insurance policies pay out if the cumulative rainfall over a certain time period falls above or below predetermined triggers. Policies were sold in units of low amounts of coverage, both to increase affordability of a small amount of coverage and to allow participants to purchase an amount of coverage suited to their individual risk profile and preference. BDM was used to elicit demand for a single unit from some participants and for a bundle of four units from other participants. The insurance policies offered varied from year to year and from weather station to weather station. The end of this Appendix contains example term sheets from 2010 and 2011.

Appendix Table 1 shows the term sheets for the Barvala Tehsil (sub-district) of Ahmedabad district in 2010. This policy offered coverage for deficit rainfall in three phases. Phase 1 lasted from June 16th to July 15th, and payouts for this phase were determined by cumulative rainfall over this period. Payouts were triggered when rainfall fell below Trigger 1 (100 mm). For every millimeter of rainfall below 100mm, the policy paid out Rs 1.25 per millimeter. When rainfall fell below Trigger 2 (50 mm), payouts per millimeter increased to Rs 7.50. The two other phases for deficit coverage worked similarly, but with different triggers and payout rates.

The policy also offered coverage for excess rainfall. This coverage paid out if any day's rainfall exceeded a certain trigger. Phase 1 lasted from September 1 to September 20 and offered Rs. 1.56 for each mm of rainfall over 80mm, up to a maximum payout of Rs. 125. Phase 2 offered a similar payout structure.

The total maximum payout for the policy was Rs. 1500, and the premium was set at Rs. 150. Because historical data at the Tehsil level does not exist (as the weather stations were only recently operational), we are unable to calculate the distribution of payouts from the policy.

B2. Weather insurance field procedures

Each year, marketing teams of SEWA employees visited SEWA members to explain rainfall insurance to them and to give them the opportunity to purchase coverage. The Centre for Microfinance provided logistical and analytical assistance to the SEWA team. Marketing took place from 2006 to 2013. BDM was first piloted in 2009 and was implemented for a large number of potential customers from 2010 to 2013.

Generally, the first part of the marketing process involved inviting all SEWA members to a village meeting where the concept of rainfall insurance and the policies that would be offered were explained. In the meetings, attendees were given the opportunity to discuss the policies and ask questions of the SEWA representatives.

Following completion of the village meetings, the SEWA marketing team returned to each village to conduct household-level marketing visits. They focused on reaching people on the pre-specified marketing list. Each person on the marketing list received a household visit by a member of SEWA's marketing team, during which they received an explanation of the insurance policy and received other (experimentally-manipulated) marketing materials. In addition, each household was given a preprinted scratch card that enabled the client to either receive fixed policy discounts or BDM. Images of the scratch cards used in 2011 and 2013 are shown in Appendix Fig. 1.

B3. Weather insurance participants

The sample consists of SEWA members who had been selected to be part of the evaluation of insurance and were therefore surveyed each year, as well as additional non-surveyed SEWA members who received insurance marketing. The non-surveyed sample is used for the BDM vs TIOLI comparison (as only this sample received TIOLI offers).

At the beginning of the project in 2006, SEWA marketed rainfall insurance in 32 villages in Gujarat (see example termsheets in Table A.1. In 2007, access was extended to 20 additional villages. These 52 villages were randomly chosen from a list of 100 villages in which SEWA had a substantial preexisting operational presence. The other 48 villages served as control villages for the parallel randomized controlled trial of the effects of rainfall insurance. Within each study village, 15 households were surveyed, of which five were randomly selected SEWA members, five had previously purchased (other forms of) insurance from SEWA, and five were identied by local SEWA employees as likely to purchase insurance. Since take-up of insurance was expected to be low, this involved purposeful oversampling of people who are more likely to purchase insurance. In 2009, 50 randomly selected SEWA members in each of eight additional villages were added to the study. Cumulatively, the sample that is part of the randomized controlled trial and assigned to receive insurance marketing by SEWA consists of 1160 households in 60 villages. To maximize power for tests involving household characteristics, only BDM procedures (for one or four policies) were assigned to surveyed households.

Additionally, SEWA marketed insurance to other members who were not part of the RCT but were identified by SEWA as potentially interested in rainfall insurance. In 2010 and 2011, this additional sample was randomly assigned either BDM (for one or four policies) or fixed-price discounts, and it is therefore used to make the comparison between BDM and TIOLI. In 2012 and 2013, this population was simply offered fixed discounts on insurance, and it is therefore not included in the BDM vs. TIOLI comparison.[27]

[27] The sample of surveyed households designated for visits remained the same from 2010 to 2014, but some households were unavailable at the time of marketing and are therefore excluded from the analysis, making the relevant sample vary slightly from year to year. The additional marketing list used for the BDM/TIOLI comparisons was also the same in 2010 and 2011, but again some households were not reached.

The total sample varies by year due to a number of factors. In the pilot year, 2009, BDM was tested on a relatively small number of households. In 2010 and 2011, BDM was assigned to all households that were surveyed as part of the RCT, while BDM or TIOLI was randomly assigned to additional households. Due to budget constraints, we offered fewer discounts to the non-RCT sample in 2011 than in 2010.

B4. Agricultural information service

The Avaaj Otalo (AO) platform is a mobile phone-based service that provides on-demand information on agricultural best practices to farmers. Information can be requested and shared by farmers who have access to this toll-free service. The service also includes weekly push-content, covering detailed weather and crop conditions, delivered through an automated voice message. A randomized controlled trial was carried out between 2010 and 2013 across 40 villages in Gujarat to understand demand for this service and its impact on a variety of agricultural outcomes. The study was conducted in partnership with the Development Support Center (DSC), an NGO with decades of experience in providing agricultural extension throughout Gujarat.

Farmers that were a part of the treatment group could avail the service without cost and ask questions on a variety of agricultural topics of relevance to them. Staff agronomists at the DSC with experience in local agricultural practices receive these requests and deliver customized advice to these farmers via recorded voice messages. Farmers may also listen to and respond to the questions their peers ask on the AO platform, which is moderated by DSC. The AO interface features a touch-tone navigation system with local language prompts, developed specifically for ease of use by semi-literate farmers.

B5. Agricultural information field procedures

In the context of this experiment, the WTP exercises were carried out at the same time as the final round of surveying was being conducted in June, 2013. So as to be able to compare the results of different price elicitation methods, these respondents were randomized into either a modified BDM implementation with discrete price points or a fixed-price, or "take it or leave it," design (hereafter, TIOLI).

The BDM WTP exercise began with a randomized marketing script. There were a total of 16 marketing scripts generated- a combination of one to four paragraphs that vary along the dimensions of whether it contains information on the service's impact on yield over the 2011 Kharif season; whether it puts an emphasis on AO's nonprofit motive; whether it highlights peer satisfaction; and whether it underscores the names of reputable local NGOs involved. Each marketing script also notified the surveyor if they were to use BDM or TIOLI. The randomization ensured that 75% of the sample was assigned to the BDM exercise, while the remaining 25% were assigned to TIOLI. The marketing team thereafter were given envelopes – each with a unique id – containing the marketing scripts along with the assigned WTP exercise for each village. Within a village, the envelopes were to be used at random for a given respondent. The WTP component was designed to last no longer than 30 min, and respondents were paid Rs. 30 in mobile top-up as compensation.

If the envelope chosen indicated that the respondent was assigned to BDM, the surveyor would read out the enclosed marketing script, obtain consent, and explain the instructions in a manner consistent with the weather insurance experiments. Following this, the surveyor offered AO to the respondent at decreasing price points, ranging from Rs. 490 to zero. If the respondent agreed to buy AO at a certain price *(bid price)*, the surveyor would then call the field office and inform the phone operator of the respondent's bid price and the unique envelope id that was used.

Having recorded the envelope id and the respondent's bid price, the phone operator would then inform the surveyor about the pre-assigned scratch card – which contained offer prices selected from Rs. 40, 90, 140, 190, and 240. The surveyor would then provide the appropriate scratch card to the respondent, who would scratch it to reveal the offer price. If the offer price was lower than the bid price quoted by the respondent, the participant would purchase the service at this discounted offer price. If the *offer price* were higher than the bid price, the procedure ended and the respondent could not purchase the AO service.

If the respondent expressed a bid greater than the offer, the surveyor collected payment and the details required to activate the service on the farmer's phone. Participation in this exercise was completely voluntary, and the respondent could choose to opt out at any point.

In the event that the envelope stated that the respondent was assigned TIOLI, the *offer price* was already included in the envelope (assigned randomly by envelope id). The surveyor then read the marketing script and obtained consent. The surveyor would then communicate to the phone operator that the respondent was assigned to TIOLI and the envelope id used. This was to ensure that there were no errors in the price communicated and that the same envelopes were not used again.

Following this, the surveyor asked the respondent if s/he would like to purchase AO at the given offer price. This offer price could take on the value of Rs. 40, 90, 140, 190, or 240. If the respondent said yes, the surveyor would then collect the money and start the process of activating the service on the respondent's phone. On the other hand, if the respondent did not want to buy the service at the given offer price, the procedure ended and they did not receive the service. As in the case of the BDM exercise, participation was completely voluntary.

B6. Agricultural information participants

The sample includes respondents spread across 40 villages in Surendranagar district in Gujarat, India. The 1200 study respondents were chosen at random from a list of over 1700 respondents who cultivated cotton, owned a mobile phone, and were the chief agricultural decision-maker in their household. From the full set of respondents who participated in the WTP experiments in 2013 were 1099, the subset of the original households who could be reached.

References

Ariely, D., Loewenstein, G., Prelec, D., 2003. coherent arbitrariness: Stable demand curves without stable preferences. Quart. J. Econ. 118 (1), 73–106.
Banerji, A., Chowdhury, S., De Groote, H., Meenakshi, J.V., Tomlins, K., Haleegoah, J., Ewool, M., et al., 2013. Using elicitation mechanisms to estimate the demand for nutritious maize: evidence from experiments in rural ghana (harvestplus working paper no. 10).
Becker, G.M., DeGroot, M.H., Marschak, J., 1964. Measuring utility by a single-response sequential method. Syst. Res. Behav. Sci. 9 (3), 226–232.
Berry, J., Fischer, G., Guiteras, R.P., 2019. Eliciting and utilizing willingness to pay: evidence from field trials in northern ghana. J. Polit. Econ..
Bohm, P., Lindén, J., Sonnegård, J., 1997. Eliciting reservation prices: Becker–Degroot–Marschak mechanisms vs. markets. Econ. J. 107 (443), 1079–1089.
Camerer, C.F., Hogarth, R.M., 1999. The effects of financial incentives in experiments: A review and capital-labor-production framework. J. Risk Uncert. 19 (1–3), 7–42.
Channa, H., Chen, A.Z., Pina, P., Ricker-Gilbert, J., Stein, D., 2019. What drives smallholder farmers willingness to pay for a new farm technology? evidence from an experimental auction in kenya. Food Policy 85, 64–71.
Cole, S., Fernando, A.N., 2019. Mobileizing agricultural advice: Technology adoption, diffusion and sustainability.
Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., Vickery, J., 2013. Barriers to household risk management: Evidence from india. Am. Econ. J. Appl. Econ. 5 (1), 104–135.
Cole, S., Stein, D., Tobacman, J., 2014. Dynamics of demand for index insurance: Evidence from a long-run field experiment. Am. Econ. Rev. Pap. Proc. 104 (5), 284–290.
Gleser, L.J., 1985. Exact power of goodness-of-fit tests of kolmogorov type for discontinuous distributions. J. Am. Stat. Assoc. 80 (392), 954–958.
Green, D., Jacowitz, K.E., Kahneman, D., McFadden, D., 1998. Referendum contingent valuation, anchoring, and willingness to pay for public goods. Resource Energy Econ. 20 (2), 85–116.
Guiteras, R.P., Jack, B.K., 2014. Incentives, selection and productivity in labor markets: Evidence from rural malawi. Technical Report. National Bureau of Economic Research.
Heffetz, O., List, J.A., 2014. Is the endowment effect an expectations effect? J. Eur. Econ. Assoc. 12 (5), 1396–1422.
Hoffmann, V., 2009. Intrahousehold allocation of free and purchased mosquito nets. Am. Econ. Rev. 99 (2), 236–241.
Horowitz, J.K., 2006. The becker-degroot-marschak mechanism is not necessarily incentive compatible, even for non-random goods. Econ. Lett. 93 (1), 6–11.
Karni, E., Safra, Z., 1987. "preference reversal" and the observability of preferences by experimental methods. Econometr. J. Econometr. Soc. 675–685.
Kőszegi, B., Rabin, M., 2006. A model of reference-dependent preferences. Quart. J. Econ. 121 (4), 1133–1165.
List, J.A., Gallet, C.A., 2001. What experimental protocol influence disparities between actual and hypothetical stated values? Environ. Resource Econ. 20 (3), 241–254.
Loewenstein, G., Adler, D., 1995. A bias in the prediction of tastes. Econ. J. 105 (431), 929–937.
Marzilli Ericson, K.M., Fuster, A., 2011. Expectations as endowments: Evidence on reference-dependent preferences from exchange and valuation experiments. Quart. J. Econ. 126 (4), 1879–1907.
Mazar, N., Koszegi, B., Ariely, D., 2014. True context-dependent preferences? the causes of market-dependent valuations. J. Behav. Decis. Making 27 (3), 200–208.
de Meza, D., Reyniers, D., 2013. Debiasing the becker–degroot–marschak valuation mechanism. Econ. Bull. 33 (2), 1446–1456.
Miller, K.M., Hofstetter, R., Krohmer, H., Zhang, Z.J., 2011. How should consumers' willingness to pay be measured? an empirical comparison of state-of-the-art approaches. J. Market. Res. 48 (1), 172–184.
Noussair, C., Robin, S., Ruffieux, B., 2004. Revealing consumers' willingness-to-pay: A comparison of the BDM mechanism and the vickrey auction. J. Econ. Psychol. 25 (6), 725–741.
Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B.P., 1992. Numerical recipes in c++. Art Sci. Comput. 2, 1002.
Schindler, R.M., Kirby, P.N., 1997. Patterns of rightmost digits used in advertised prices: implications for nine-ending effects. J. Consumer Res. 24 (2), 192–201.
Simonson, I., Drolet, A., 2004. Anchoring effects on consumers' willingness-to-pay and willingness-to-accept. J. Consumer Res. 31 (3), 681–690.
Tobacman, J., Stein, D., Shah, V., Litvine, L., Cole, S., Chattopadhyay, R., 2016. Reduced-form impacts of formal insurance against weather shocks.
Yishay, A.B., Fraker, A., Guiteras, R., Palloni, G., Shah, N.B., Shirrell, S., Wang, P., 2017. Microcredit and willingness to pay for environmental quality: Evidence from a randomized-controlled trial of finance for sanitation in rural cambodia. J. Environ. Econ. Manag. 86, 121–140.